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Measuring the vulnerability of global airline alliances to member exits

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Abstract

We analyse the vulnerability of airline alliance route networks to the exit of member airlines. Vulnerability measures how easy it is to disconnect a network. The assessment is performed by applying the theory of complex networks. We compute the normalized vulnerability for Star Alliance, oneworld and SkyTeam using airline schedules data and derive a ranking of member airlines according to their share in the overall vulnerability of the respective alliance. One result of our paper is that oneworld is the most vulnerable global airline alliance, SkyTeam ranks second, followed by Star Alliance.

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Keywords: Global airline alliances; airline route networks; network vulnerability; complex networks

1. Introduction

The restructuring of airline activities into alliances has been one of the major traits of this industry since Star Alliance was founded in 1997. The number of members in all three global airline alliances (Star Alliance, oneworld and SkyTeam) has increased considerably over the years. The larger number of members is associated with a higher risk of defection. In 2014, Star Alliance lost two member airlines (US Airways and TAM) after these carriers merged with airlines from oneworld. Such an exit of partner airlines can be a precarious problem for airline alliances, e.g. in the form of sunk costs due to alliance-specific investments or the risk that former alliance members use confidential information to their competitive advantage. Further, it implies a decrease in network coverage.

Airline alliances provide global connectivity based on codesharing agreements between member airlines. The aim is that an airline alliance route network (AARN) appears to be an extension of each partner's network (Park and

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Zhang, 1998). Codesharing in combination with coordinated flight schedules allows the provision of continuous services for passengers connecting between airlines. With the extensive use of this practice, codesharing has become the hallmark of the alliance revolution in the aviation industry (Lordan et al., 2014a). It allows airlines to offer routes without operating them which is cost-efficient. Avoiding overlapping operations also implies less competition. The drawback is a dependency on partner airlines. A member exit leads to the deletion of routes (if not operated by other alliance members) which affects an alliance's global connectivity. Not all member exits have the same impact because some airlines contribute more to an AARN than others. Therefore, it is an important issue for the managing bodies of an alliance how to accurately assess the impact of a (potential) exit of a given member airline (e.g. in case of bankruptcy) and similarly, how to develop an AARN with appropriate partner selection. This paper studies the vulnerability of airline alliances to member exits. We propose measures that can be instrumental in assessing the dependency of an alliance on a member's route network and can also serve to develop a more resilient AARN.

The effects of airline alliances on traffic volumes, fares, and welfare have been studied by several researchers (e.g. Park, 1997; Brueckner, 2001; Zou et al., 2011). The trade-off between alliance benefits and risks has been analysed by Kleymann and Seristö (2001). Recently, Garg (2016) presented a model based approach to select strategic alliance partners. Different reasons for a company to leave an inter-firm co-operation are discussed by Sroka and Hittmár (2013). Our research adds to the literature on global airline alliances by quantifying the potential damage for airline alliance route networks caused by member exits. AARNs combine route networks of individual airlines. Hence, AARNs can be considered as multi-layered networks (Cardillo et al., 2013) that constitute an intermediate level of air transport networks between individual airline networks and the industry network (Lordan et al., 2014a). Vulnerability measures how easy it is to disconnect a network. The study of air transport networks includes the topological analysis of global (e.g. Guimerà and Amaral, 2004; Guimerà et al., 2005; Lordan et al., 2014b) and regional (e.g. Bagler, 2008; Zhang et al., 2010) route networks. Vulnerability has been investigated for global (e.g. Lordan et al., 2014b), regional (e.g. Chi and Cai, 2004) and airline alliance (Lordan et al., 2015) route networks.

In this paper, we analyse the vulnerability of AARNs as real world networks building on the theory of complex networks (Estrada, 2011; Estrada and Knight, 2015). More specifically, we measure AARN vulnerability using the concept of normalized average edge betweenness (Mishkovski et al., 2011; Lordan et al., 2015). AARNs are constructed as an aggregation of the airlines' route networks belonging to the alliance. Data comes from the OAG airline schedules database. The proposed methodology provides a normalized measure of the vulnerability of a given AARN to (potential) member exits. One result of applying this measure is that oneworld is the most vulnerable AARN, SkyTeam ranks second and Star Alliance is the most robust AARN. Further, the paper indicates a positive relation between network robustness and route overlaps among members of global airline alliances. We also rank member airlines according to their contribution to the overall AARN vulnerability. Our paper shows that the size of a carrier's scheduled operation is not strictly related to the carrier's importance for the vulnerability of an airline alliance route network.

2. Methodology

On principle, the analysis of network vulnerability assesses the stability and robustness of the global behaviour of complex network dynamics under external perturbations (Boccaletti et al. 2007). In this paper, airline networks are defined as airports (nodes) connected by operated routes (edges) and treated as undirected and unweighted networks, i.e., two airports are linked if an alliance member has one operating flight between them. Our approach is consistent with studies of the global air transport network (e.g. Guimerà and Amaral, 2004; Guimerà et al., 2005; Lordan et al., 2014b) and airline alliance route networks (Lordan et al., 2015) that assume networks to be undirected and unweighted in order to focus on network connectivity. We only consider operating flights and exclude codesharing flights from our analysis.

Average edge betweenness of the graph G is defined as (Boccaletti et al., 2007)

$$b(G) = \frac{1}{|E|} \sum_{l \in E} b_l \tag{1}$$

where |E| is the number of edges and b_l is the edge betweenness of the edge l defined as

$$b_l = \sum_{i \neq j} \frac{n_{ij}(l)}{n_{ij}} \tag{2}$$

where $n_{ij}(l)$ is the number of geodesics (shortest paths) from node i to node j that contain the edge l, and n_{ij} is the total number of shortest paths between i and j. If N represent the number of nodes of a network, then the b(G) values for a complete graph and a path graph are

$$b\big(G_{complete}\big) = 1 \qquad \text{and} \qquad b\big(G_{path}\big) = \frac{N(N+1)}{6} \tag{3}$$

and, hence, $b(G_{complete}) \leq b(G) \leq b(G_{path})$. G is more robust than G', if $b(G) < b(G')$. The normalized average edge betweenness of a network is defined as (Mishkovski et al., 2011)

$$b_{nor}(G) = \frac{b(G) - b(G_{complete})}{b\big(G_{path}\big) - b(G_{complete})} = \frac{b(G) - 1}{\frac{N(N+1)}{6} - 1} \tag{4}$$

where $b_{nor}(G)$ ranges from 0 (i.e., the most robust network) to 1 (i.e., the most vulnerable network). Thus, $b_{nor}(G)$ is a normalized measure of network vulnerability. The contribution of a member airline to the overall vulnerability of an AARN can then be calculated as the relative difference of the normalized average edge betweenness, that is

$$D_{member} = \frac{b_{nor}(G') - b_{nor}(G)}{b_{nor}(G)} \tag{5}$$

where G' is the graph obtained from G (i.e., the entire AARN) after removing the edges of the exiting member airline which are not operated by any other member. A positive value of D_{member} implies that the AARN becomes more vulnerable. The higher the value of D_{member} the more negatively affected is the AARN by the exit of the respective airline. A negative value of D_{member} would mean that a member exit is actually decreasing the AARN vulnerability, i.e., the alliance is more robust without this airline.

3. Results

We analyse the three global airline alliances using OAG airline schedules data for the week ending September 8, 2014. In this period, Star Alliance had 27 member airlines, SkyTeam 20, and oneworld 15 as shown in Appendix A. In Figure 1 we rank member airlines of Star Alliance, SkyTeam and oneworld based on their contribution to the overall vulnerability of the respective alliance, i.e., according to their D_{member} value. ALL (with value 0) refers to the entire AARN without any exit.

A carrier's share in the overall vulnerability of an alliance is not comparable between alliances as the D_{member} values are normalized against the average edge betweenness b(G) of the graph G, i.e., the entire AARN and not the most important airline of an AARN or of all three alliances. The impact of United Airlines (UA) on the Star Alliance route network is comparatively larger than the one of American Airlines (AA) on oneworld's AARN despite its smaller D_{member} value. This is illustrated in Figure 1 by the length of the bars representing UA and AA in relation to the bars of the other carriers of Star Alliance and oneworld, respectively.

Table 1 provides the values of the average edge betweenness b(G'), the normalized average edge betweenness $b_{nor}(G')$, and relative difference of the normalized edge betweenness D_{member} for each member airline. For ALL, b(G') and $b_{nor}(G')$ equal b(G) and $b_{nor}(G)$, respectively, as ALL stands for the AARN without any member removal. The $b_{nor}(G)$ value ALL = 0.0438 for oneworld's entire network is larger than the respective values for SkyTeam and Star alliance which makes it the most vulnerable among the three AARNs. While the values of D_{member} and $b_{nor}(G')$ represent a one-to-one mapping, i.e., a higher (lower) value of D_{member} is strictly related to a higher (lower) value of $b_{nor}(G')$, this is not the case for the relation between D_{member} and b(G'). For example, the $b_{nor}(G')$ of the Star Alliance members United Airlines (UA) and Turkish Airlines (TK) are 0.00277 and 0.00243, respectively, while the values for b(G') have a reverse order (445.9 and 517.4). The average edge betweenness does not account for the change in the number of airport nodes of an AARN resulting from a member exit. This is the reason why D_{member} is computed as the relative difference of the normalized average edge betweenness of an AARN with and without a given member airline.

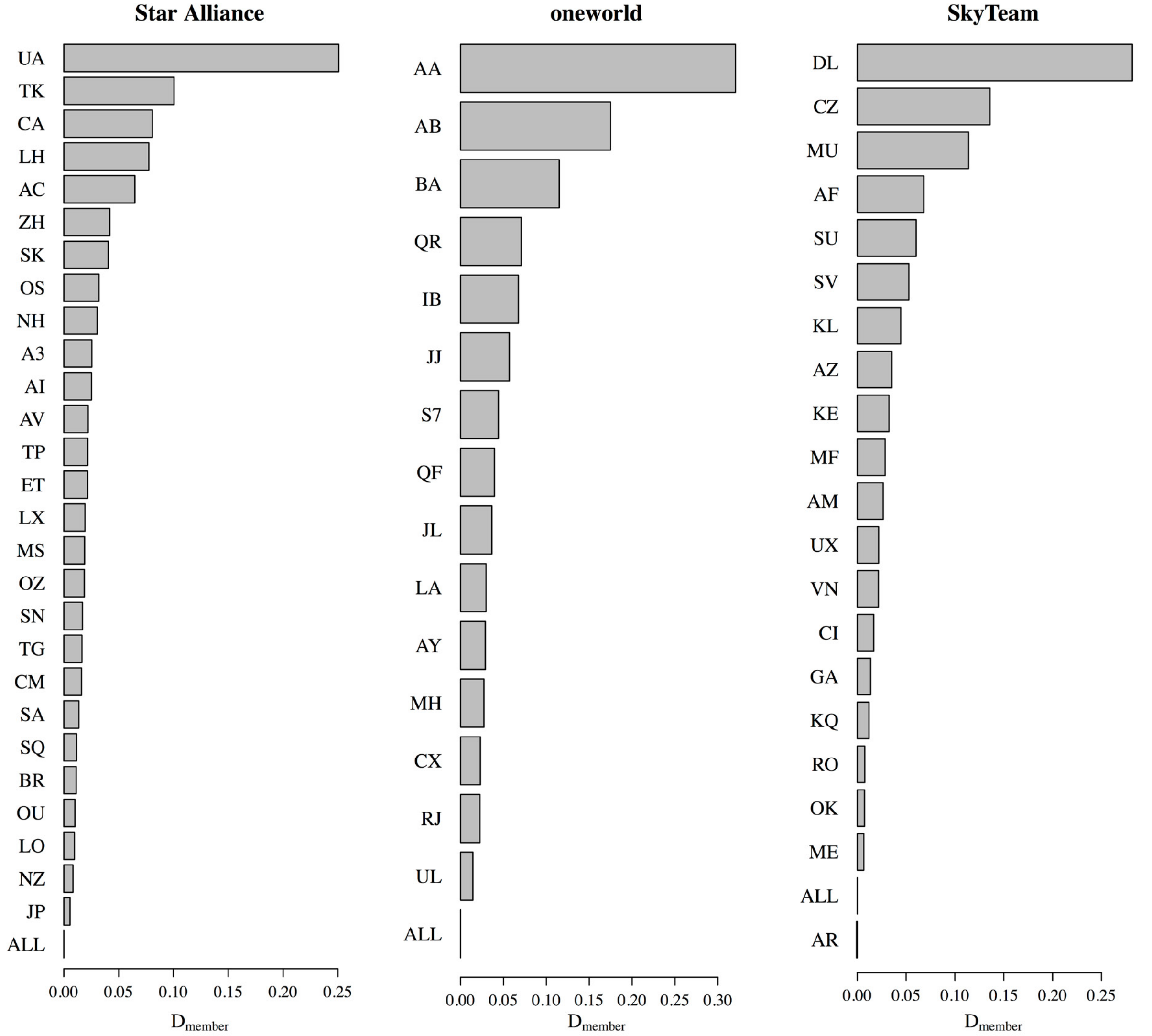

Fig. 1. Vulnerability of global airline alliances to member exits ranked by D_{member}.

Table 2 provides the values for nodes N, edges E, shared nodes S_N, and shared edges S_E of each member airline. S_N and S_E stand for the number of airport and route duplicates in an AARN with other member airlines out of the total alliance nodes and edges. All non-shared nodes and edges of an airline, i.e., all airports and routes not operated by any other alliance member will be removed from their AARN if this airline leaves the alliance. For ALL, S_N and S_E stand for all duplicates among its members out of the total alliance nodes and edges. That the S_N and S_E percentages for ALL are lowest for oneworld (S_N=29.0% and S_E=3.5% for ALL) is a network property that contributes to the higher vulnerability of oneworld measured by D_{member} in comparison to the more robust alliance networks. Similarly, the total AARN egde-to-node ratio of oneworld is 2.6 (2,251 edges divided by 852 nodes) which is considerably below the ratio of 3.6 for the two other global airline alliances.

The exit of the respective US member airline would have the biggest impact on the AARN of all three alliances, because many routes offered by the US carriers are not operated by any other alliance member. For example, Delta Air Lines (DL) only operates S_E=2.0% overlapping routes and a small percentage S_N=29.8% of airport duplicates with other member airlines from oneworld. Clearly, this is due to the large domestic network offered by the US carriers.

Table 1. Comparison of different vulnerability measures of global airline alliances ranked by D_{member}.

Star Alliance	b(G')	b_{nor}(G')	D_{member}	**SkyTeam**	b(G')	b_{nor}(G')	D_{member}	**oneworld**	b(G')	b_{nor}(G')	D_{member}
UA	445.9	0.00277	0.251	DL	382.2	0.00338	0.282	AA	443.2	0.00578	0.320
TK	517.4	0.00243	0.101	CZ	521.1	0.00300	0.136	AB	568.3	0.00514	0.175
CA	529.1	0.00239	0.081	MU	499.2	0.00294	0.114	BA	552.7	0.00488	0.115
LH	561.8	0.00238	0.078	AF	489.1	0.00282	0.068	QR	529.5	0.00469	0.071
AC	516.7	0.00235	0.065	SU	461.2	0.00280	0.060	IB	536.9	0.00467	0.067
ZH	550.7	0.00230	0.042	SV	469.0	0.00278	0.053	JJ	517.6	0.00463	0.057
SK	525.5	0.00230	0.041	KL	488.7	0.00276	0.044	S7	483.1	0.00457	0.044
OS	539.1	0.00228	0.032	AZ	483.5	0.00273	0.035	QF	487.0	0.00455	0.040
NH	520.3	0.00228	0.030	KE	492.5	0.00272	0.032	JL	500.3	0.00454	0.037
A3	542.0	0.00227	0.026	MF	498.2	0.00271	0.029	LA	472.9	0.00451	0.030
AI	508.9	0.00227	0.025	AM	464.6	0.00271	0.027	AY	525.0	0.00450	0.029
AV	516.2	0.00226	0.022	UX	479.0	0.00270	0.022	MH	499.5	0.00450	0.027
TP	527.6	0.00226	0.022	VN	478.9	0.00270	0.022	CX	540.9	0.00448	0.023
ET	527.5	0.00226	0.022	CI	491.5	0.00268	0.017	RJ	535.6	0.00448	0.023
LX	542.4	0.00225	0.019	GA	448.0	0.00267	0.014	UL	535.1	0.00444	0.014
MS	536.7	0.00225	0.019	KQ	476.3	0.00267	0.012	**ALL**	**531.2**	**0.00438**	**0**
OZ	530.3	0.00225	0.019	RO	479.7	0.00266	0.008				
SN	533.0	0.00225	0.017	OK	487.0	0.00266	0.007				
TG	531.9	0.00225	0.017	ME	482.0	0.00266	0.007				
CM	538.0	0.00225	0.016	**ALL**	**486.2**	**0.00264**	**0**				
SA	511.9	0.00224	0.014	AR	450.5	0.00264	-0.001				
SQ	538.3	0.00224	0.012								
BR	537.2	0.00224	0.011								
OU	536.6	0.00223	0.010								
LO	537.2	0.00223	0.010								
NZ	507.5	0.00223	0.008								
JP	535.1	0.00222	0.006								
ALL	**532.9**	**0.00221**	**0**								

Table 2. Member network properties ranked by D_{member} (N: Nodes; E: Edges; S_N: Shared nodes; S_E: Shared edges).

Star Alliance	N	E	S_N	S_E	**SkyTeam**	N	E	S_N	S_E	**oneworld**	N	E	S_N	S_E
UA	371	906	41.0%	4.6%	DL	325	845	29.8%	2.0%	AA	264	506	33.7%	5.1%
TK	255	369	71.4%	5.1%	CZ	191	637	84.3%	33.1%	AB	109	337	64.2%	2.1%
CA	164	337	69.5%	19.3%	MU	200	571	79.0%	32.2%	BA	185	230	84.3%	7.0%
LH	203	313	93.6%	16.6%	AF	169	219	81.7%	9.6%	QR	132	131	77.3%	5.3%
AC	163	286	66.3%	5.9%	SU	145	224	60.7%	6.3%	IB	103	134	77.7%	11.9%
ZH	67	211	92.5%	16.6%	SV	92	205	51.1%	2.9%	JJ	62	151	45.2%	9.3%
SK	105	198	69.5%	8.6%	KL	136	142	85.3%	12.7%	S7	90	120	36.7%	1.7%
OS	120	141	90.0%	11.3%	AZ	94	138	77.7%	11.6%	QF	75	132	30.7%	6.8%
NH	90	177	64.4%	13.6%	KE	109	138	90.8%	26.1%	JL	74	119	45.9%	9.2%
A3	66	118	92.4%	9.3%	MF	64	192	96.9%	47.4%	LA	90	139	33.3%	12.2%
AI	84	158	50.0%	7.0%	AM	77	120	51.9%	2.5%	AY	69	69	75.4%	4.3%
AV	87	156	63.2%	12.8%	UX	53	93	64.2%	4.3%	MH	80	110	53.8%	4.5%
TP	88	109	78.4%	8.3%	VN	52	98	63.5%	9.2%	CX	52	59	96.2%	25.4%
ET	88	113	78.4%	12.4%	CI	64	78	95.3%	24.4%	RJ	54	55	88.9%	7.3%
LX	79	100	98.7%	19.0%	GA	71	125	31.0%	7.2%	UL	34	39	91.2%	15.4%
MS	73	87	90.4%	8.0%	KQ	51	62	66.7%	6.5%	**ALL**	**852**	**2251**	**29.0%**	**3.5%**
OZ	85	102	83.5%	21.6%	RO	41	44	73.2%	11.4%					
SN	76	87	86.8%	14.9%	OK	36	37	91.7%	21.6%					
TG	76	83	85.5%	21.7%	ME	35	36	77.1%	11.1%					
CM	67	85	94.0%	22.4%	**ALL**	**1050**	**3732**	**34.2%**	**8.8%**					
SA	65	87	50.8%	5.7%	AR	55	84	29.1%	4.8%					
SQ	63	64	98.4%	31.3%										
BR	52	58	96.2%	17.2%										
OU	30	52	93.3%	15.4%										
LO	50	49	98.0%	16.3%										
NZ	51	92	33.3%	2.2%										
JP	22	24	95.5%	4.2%										
ALL	**1201**	**4305**	**39.4%**	**5.7%**										

4. Discussion

The normalized average edge betweenness for the entire route network of oneworld is larger than the respective ALL-values for SkyTeam and Star Alliance. Hence, oneworld's network is more vulnerable to member exits than the other two AARNs. This is reflected by the average D_{member} values (Star Alliance 0.038, SkyTeam 0.049, and 0.071 for oneworld) and also the maximum D_{member} values (Star Alliance 0.251, SkyTeam 0.282, and 0.320 for oneworld). Intuitively, one might ascribe this difference in AARN vulnerability to the different percentages of shared nodes S_N among all nodes. 39.4% of all 1,201 weekly scheduled airports operated by Star Alliance in September 2014 are duplicates, 34.2% out of 1,050 at SkyTeam and only 29.0% out of 852 at oneworld (see Table 2). This suggests higher average D_{member} values for oneworld. Likewise, low percentages of shared edges S_E increase

D_{member} indicating higher AARN vulnerability. oneworld has the lowest S_E percentage with 3.5%, while S_E percentages for Star Alliance and SkyTeam are 5.7% and 8.8% respectively.

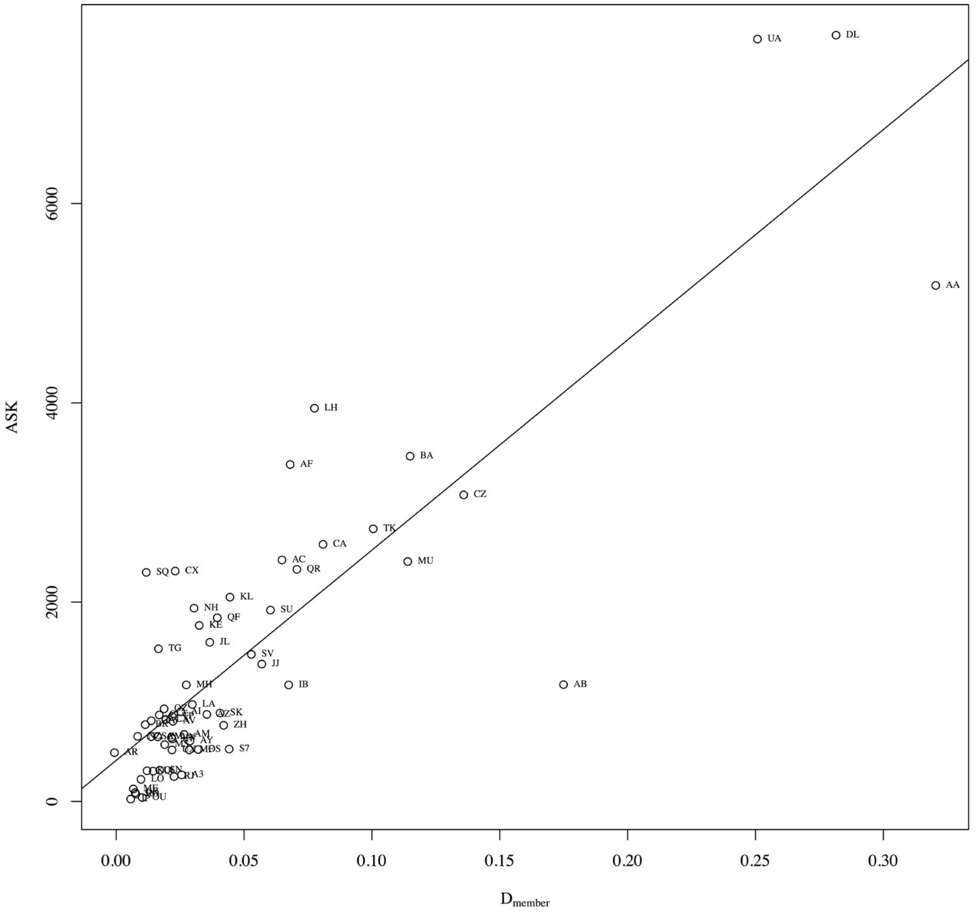

Fig. 2. Correlation between ASK (in millions) and D_{member}.

Table 2 shows that the total number of airports and routes offered by a member airline also affects its share in the AARN vulnerability. Alliance members operating larger networks with many routes and airports tend to also have higher D_{member} values which is intuitively plausible. However, there is no one-to-one relation between the total number of nodes or edges and D_{member} values.

In all three alliances the exit of the US member airline (UA, DL, or AA) would have the biggest impact on the AARN. These are also the largest carriers within each alliance based on available seat kilometres (ASKs). However, Figure 2 indicates that the size of a carrier's scheduled operation measured by ASKs is not strictly related to the carrier's importance for the AARN robustness. For example, measured by D_{member}, Air Berlin (AB) is more important than British Airways (BA) for the AARN of oneworld. Similarly, D_{member} values for China Eastern (MU) and China Southern Airlines (CZ) for Skyteam's route network are larger than the value for Air France (AF) despite of lower ASKs.

While BA offers more than twice as much ASKs as AB, the D_{member} of BA is considerable lower than the one of AB. Hence, when considering AARN vulnerability only, an exit of AB would hurt oneworld more than the departure of BA. The network of BA contains 185 airports while AB flies to 109 airports (see Table 2). S_N=64.2% (70 airports) of all airports served by AB are duplicates that are also served by other members of oneworld, while for BA the percentage is S_N=84.3% (156 airports). Hence, despite an overall smaller airport network, AB operates to more airports exclusively than BA (39 to 29). When it comes to the number of operated routes, AB offers 337 and

BA only 230. Obviously, comparing just these two numbers can be misleading as they do not account for essential capacity parameters such as frequencies and aircraft sizes. However, that AB operates 330 of its routes exclusively, i.e., without route overlaps with other oneworld members, while the number of non-shared routes of BA is only 214 partially explains the higher D_{member} value of AB in comparison with BA.

In general, one would think that airlines adding additional airport duplicates and route overlaps to a global airline alliance should strengthen the robustness of an AARN. However, this is not always the case. For instance, Aerolineas Argentinas (AR) and Garuda Indonesia (GA) have similar network properties, but AR makes SkyTeam more vulnerable while GA makes it more robust. The opposite effect of AR and GA on the robustness of SkyTeam despite similar network properties indicates the complexity of airline alliance route networks.

It is essential to remember that D_{member} values are normalized against the average edge betweenness b(G) of the graph G, i.e., the entire AARN and not the most important airline of an AARN or of all three AARNs. The average D_{member} values for Star Alliance and SkyTeam are smaller than for oneworld because oneworld has a more balanced membership, i.e., relatively less dominant airlines with many routes offered by no other member airline and also fewer small airlines relative to the largest airline in the alliance. Furthermore, all else equal the larger the number member airlines the smaller is the average D_{member} value of an alliance. Hence, it is not surprising that oneworld with the smallest number of members is more vulnerable to member exits than Star Alliance and SkyTeam. Similarly, this also contributes to AA's D_{member} being larger than UA's despite AA being smaller than UA when the carrier size is measured by ASKs.

As a runner-up to UA, Turkish Airlines (TK) contributes significantly to the robustness of Star Alliance, even more than Lufthansa (LH) (see Figure 2). A carrier's size obviously is important but the size is adjusted by the number of overlapping routes with other alliance members. Lordan et al. (2014) point out that member selection of global alliances is influenced by the route potential, i.e., preferred new partners offer complementary routes not operated by an alliance airline before. However, if alliances look for new members providing robustness to the AARN they should also increase the number of route overlaps. A new member airline having many route overlaps with other alliance members reduces the overall network vulnerability but also increases intra-alliance competition. This might lead to negative consequences for the partner airlines, e.g. lower average fare levels.

5. Conclusions

How to assess the impact of a (potential) exit of a member airline and how to build a robust airline alliance route network (AARN) with appropriate partner selection are two critical issues for the managing bodies of global airline alliances. This paper proposed a methodology to assess the vulnerability of AARNs to member exits. The derived measure of a member share in the overall vulnerability can also be used to assess a new member's contribution to the robustness of an AARN.

Applying the vulnerability measure to the flight schedules of Star Alliance, SkyTeam and oneworld shows that that oneworld is the most vulnerable AARN, followed by SkyTeam and then Star Alliance. Further, the size of a carrier's scheduled operation is not strictly related to the carrier's importance for the robustness of an AARN. However, the exit of the large US carriers United Airlines (UA), Delta Air Lines (DL) and American Airlines (AA) would have the biggest impact on of the respective airline grouping as there are many routes offered by these American carriers not operated by any other alliance member. In June 2015, Qatar Airways questioned the company's oneworld alliance membership as a consequence of the dispute between US and Gulf carriers over government subsidies. Based on our analysis such a move by the carrier would have a significant negative impact on oneworld's network as Qatar Airways has the fourth largest member share in the overall vulnerability of this alliance.

One limitation of our paper is that routes are not weighted. Hence, in future research some thoughts should be given to a weighting scheme of airline routes considering frequency and seat capacity. It would be also interesting to assess the reverse of a member exit: What happens in terms of reduced network vulnerability if a given airline joins an alliance? Future work might also investigate the optimal robustness of an airline alliance route network, i.e., the trade-off between network vulnerability and overlapping networks, which should be of interest to airline managers.

Appendix A. Alliances and member airlines

ALL	Star Alliance	ALL	SkyTeam	ALL	oneworld
A3	Aegean Airlines	AF	Air France	AA	American Airlines
AC	Air Canada	AM	Aeromexico	AB	Air Berlin
AI	Air India	AR	Aerolineas Argentinas	AY	Finnair
AV	Avianca	AZ	Alitalia	BA	British Airways
BR	EVA Airways	CI	China Airlines	CX	Cathay Pacific Airways
CA	Air China	CZ	China Southern Airlines	IB	Iberia
CM	Copa Airlines	DL	Delta Air Lines	JJ	TAM Linhas Aereas
ET	Ethiopian Airlines	GA	Garuda Indonesia	JL	Japan Airlines
JP	Adria Airways	KE	Korean Air	LA	Lan Airlines
LH	Lufthansa German Airlines	KL	KLM-Royal Dutch Airlines	MH	Malaysia Airlines
LO	LOT - Polish Airlines	KQ	Kenya Airways	QF	Qantas Airways
LX	Swiss	ME	Middle East Airlines	QR	Qatar Airways
MS	Egyptair	MF	Xiamen Airlines Company	RJ	Royal Jordanian
NH	All Nippon Airways	MU	China Eastern Airlines	S7	S7 Airlines
NZ	Air New Zealand	OK	Czech Airlines	UL	Srilankan Airlines
OS	Austrian Airlines	RO	Tarom		
OU	Croatia Airlines	SU	Aeroflot Russian Airlines		
OZ	Asiana Airlines	SV	Saudi Arabian Airlines		
SA	South African Airways	UX	Air Europa		
SK	SAS Scandinavian Airlines	VN	Vietnam Airlines		
SN	Brussels Airlines				
SQ	Singapore Airlines				
TG	Thai Airways International				
TK	Turkish Airlines				
TP	TAP Portugal				
UA	United Airlines				
ZH	Shenzhen Airlines				

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